

Understanding User Instructions by Utilizing Open Knowledge for Service Robots

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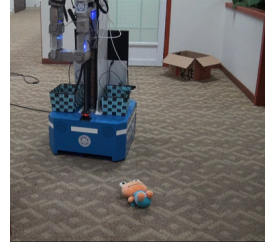
Abstract—Understanding user instructions in natural language is an active research topic in AI and robotics. Typically, natural user instructions are high-level and can be reduced into low-level tasks expressed in common verbs (e.g., ‘take’, ‘get’, ‘put’). For robots understanding such instructions, one of the key challenges is to process high-level user instructions and achieve the specified tasks with robots’ primitive actions. To address this, we propose novel algorithms by utilizing semantic roles of common verbs defined in semantic dictionaries and integrating multiple open knowledge to generate task plans. Specifically, we present a new method for matching and recovering semantics of user instructions and a novel task planner that exploits functional knowledge of robot’s action model. To verify and evaluate our approach, we implemented a prototype system using knowledge from several open resources. Experiments on our system confirmed the correctness and efficiency of our algorithms. Notably, our system has been deployed in the KeJia robot, which participated the annual RoboCup@Home competitions in the past three years and achieved encouragingly high scores in the benchmark tests.

Index Terms—Service Robots, Human-Robot Interaction, Natural Language Understanding and Task Planning.

I. INTRODUCTION

NOWADAYS, service robots can do more and more work in our daily life, such as moving around in a house, fetching drink or medicine for elderly people, or preparing food for a family. They are smart and can do many complex tasks autonomously. Nevertheless, when robots encounter user requests or tasks in an open-ended form (e.g., through dialogs in natural language), they often fail to response properly, not only due to possible language processing failures but also the challenges of task planning with incomplete knowledge. For example, as illustrated in Figure 1, a daily instruction “clean up toys” is challenging for a robot to process if the action “clean up” is *under-specified* and “have a headache” is also nontrivial for a robot to offer help to people without grounding the helping verb (i.e., knowing how to help). These are common tasks in domestic scenarios and therefore it is desirable for service robots to be able to complete such tasks given user instructions in natural language.

Typically, user instructions are *action-directed* in the sense that the fundamental purpose of an instruction is to specify what users want a robot to do for them. This indicates a connection between robot understanding (i.e., knowing what the users said) and acting (i.e., doing what the users asked). In other words, understanding an instruction means that the robot is able to generate a plan (i.e., sequence of actions) for the tasks specified in the instruction [1], [2], [3], [4], [5], [6]. Therefore, it is crucial for the robot to have the knowledge about the tasks and actions in order to do planning. However,



- Task:
 - Clean up toys
- Steps:
 - Pick up toys from floor
 - Put toys in the toybox

(a) Clean up toys



- Desire:
 - Have a headache
- Actions:
 - Give him an aspirin
 - With pain medication

(b) Have a headache

Fig. 1. Examples of robot tasks for user instructions in natural language.

some knowledge may be missing in the instruction (e.g., “have a headache” does not directly indicate that the robot should give the user an aspirin). Consequently, the robot does not know how to act when such instructions are presented.

Fortunately, there is more and more common knowledge available in open resources, such as the *Open Mind Indoor Common Sense* (OMICS) database [7], *wikihow*¹, *WordNet*, and many other digital dictionaries. In these dictionaries, actions are often *hierarchical* where a high-level action is composed of several lower-level actions. Similarly, user instructions are often specified hierarchically in which an action is referred by an action verb or verb phrase. For instance, “clean up a house” may indicate a series of subtasks such as “clean the table”, “clean the floor”, etc. Therefore, common-sense knowledge about hierarchical relations between tasks and subtasks is useful for instruction understanding.

In our previous studies [8], we found that a user instruction representing a high-level task can usually be reduced into a sequence of low-level subtasks, using hierarchical knowledge in open resources. Furthermore, we observed that this reduction procedure often ends up at so-called primitive tasks (i.e., low-level subtasks expressed in *common verbs* [9]). For instance, in OMICS, “serve a drink from fridge” is reduced into a sequence of low-level subtasks expressed in common verbs, such as “go to fridge”, “open the fridge door”, and “take the drink”, where ‘go’, ‘open’, and ‘take’ are common verbs. Ideally, if all of the primitive tasks in the reduction can be directly mapped into robot’s actions, the robot can simply complete the task by executing those actions.

However, it is generally nontrivial to map primitive tasks

¹<http://www.wikihow.com>

to robot's actions. One of the key challenges is that there is little knowledge about *common verbs* in most open resources and furthermore how they can be executed by robot with its actions. To avoid this challenge, most of the existing approaches [3], [4], [10] manually create a small set of hand-coded robot actions for primitive tasks though their scalability (i.e., only work for small problems) and generality (i.e., only work for specific domains) are limited. To build a *general-purpose* system for handling *large-scale* user instructions, we directly tackle this challenge and consider the follow problems: 1) how to define semantics of meanings of common verbs, match and recover such semantics in user instructions and 2) how to handle a large number of instructions and generate plans in realtime using open knowledge resources.

To address these problems, we propose a novel system for service robots to 1) process user instructions based on semantic roles of common verbs defined in semantic dictionaries, and 2) then generate plans for the corresponding tasks of user instructions. The semantic roles suggest possible entities in the knowledge representation that may be missing from or omitted in natural instructions. In more detail, we introduce a heuristic method to match and recover missing semantic roles from the context of user instructions. Then, we use a planner based on *Answer Set Programming* (ASP) [11] to exploit definitions of common verbs in terms of semantic roles and generate a plan for the task specified in the user instruction. By putting them together, we built a general-purpose system for service robots that can handle large-scale user instructions using open commonsense knowledge.

To evaluate our approach, we conducted a corpus-based experiment on two test sets with 11885 user tasks and 467 user desires collected from OMICS. We also developed a prototype system and ran a case study on a service robot in two typical domestic scenarios. Our experimental results show substantial improvement in performance on user instruction understanding. It is worth pointing out that the proposed system has been successfully deployed in our KeJia² robot, which participates annually RoboCup@Home³ competition and won the first place once and the second place twice in the pass three years. During the benchmark tests of the RoboCup@Home competitions, our system is used by our robot for understanding the instructions in English given by referees and completing the corresponding tasks. This confirms the usefulness of our system in practice.

The remainder of this article is organized as follows. Section II introduces our problem and Section III presents an overview of our system. Then, Section IV proposes our main algorithms, followed by Sections V and VI describing the two key techniques used in our algorithms. Next, Section VII reports our experimental results. Finally, Section VIII briefly reviews the related work and Section IX concludes.

II. PROBLEM STATEMENT

We aim to building a general-purpose system so that the robot can understand user instructions and provide service for the

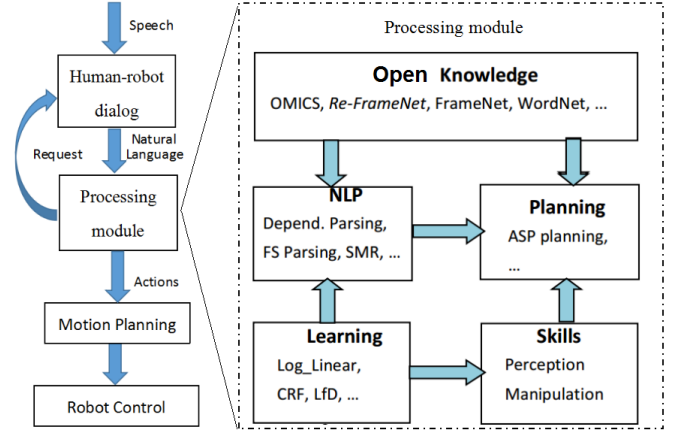


Fig. 2. System architecture.

user. To this end, we must solve the problem of generating a sequence of primitive actions, which can be directly executed by a robot, given user instructions in natural language. For example, when a user says: “please serve a meal for me”, the robot will take the meal, put it on a plate, and place the plate on a table; when a user says: “I am thirsty”, the robot will take a drink from the fridge and deliver it to the user. To achieve this, our system must be able to extract a task from a user instruction in natural language (i.e., knowing what the user said) and generate a executable plan for the task (i.e., doing what the user asked). In other words, natural language understanding and task planning must be combined systematically in order to solve our problem.

In the next section, we give an overview of our system for instruction understanding and task planning that is built by integrating different modules.

III. SYSTEM OVERVIEW

The overall architecture of our system is shown in Figure 2. As we can see, the human-robot dialog system transcribes spoken utterances into text sentences and manages the dialog with users. Each sentence in the dialog is then transferred to the processing module, which generates a sequence of primitive actions for the task expressed in natural language. After that, a sequence of commands corresponding to each primitive action is computed by the Motion Planning module. Finally, the commands are executed by the Robot Control module.

Here, we focus on the *Processing module* that takes a text sentence as its input and outputs a sequence of primitive actions that are executable by the robot. The main components of our Processing module are described in detail as follows.

A. Open Knowledge

As shown in Figure 2, we use open knowledge both for *Natural Language Processing* (NLP) and task planning. The *Open Knowledge* considered in our system includes OMICS, *FrameNet*, and *Re-FrameNet* as introduced below.

OMICS [7] is an extensive collection of knowledge for indoor service robots gathered from internet users. Currently, it contains 48 tables capturing different sorts of knowledge,

²<http://ai.ustc.edu.cn/en/robocup/atHome/index.php>

³<http://www.robocup.org/robocup-home/>

among which the *Help* and *Tasks/Steps* tables are most useful for our system. Each tuple of the *Help* table maps a user desire to a task that may meet the desire (e.g., \langle “feel thirsty”, “by offering drink” \rangle). Each tuple of the *Tasks/Steps* table decomposes a task into several steps (e.g., \langle “serve a drink”, 0. “get a glass”, 1. “get a bottle”, 2. “fill glass from bottle”, 3. “give glass to person” \rangle). Given this, OMICS offers useful knowledge about hierarchism of naturalistic instructions, where a high-level user request (e.g., “serve a drink”) can be reduced to lower-level tasks (e.g., “get a glass”, \dots). Another feature of OMICS is that elements of any tuple in an OMICS table are semantically related according to a predefined template. This facilitates the semantic interpretation of the OMICS tuples.

*FrameNet*⁴ is a digital dictionary providing rich semantic information for action verbs. It groups action verbs into *Frames* and specifies word definitions in terms of semantic roles called *Frame Elements* (FEs) for each Frame [12]. Although the connections between an action verb and its semantic roles are useful for resolving under-specification of naturalistic instructions, this knowledge cannot be directly used by robots since it is not formalized in *FrameNet*. To overcome this difficulty, we developed *Re-FrameNet* — a formalized version of *FrameNet* by rewriting part of *FrameNet* knowledge in a formal meta-language.

Specifically, in *Re-FrameNet*⁵, a Frame of *FrameNet* is formalized as a meta-task and re-defined by a set of precondition, postcondition, invariant, and/or steps over semantic roles of the meta-task. In the definition, FEs (i.e., semantic roles) such as *Theme*, *Source*, and *Goal* of the Frame are taken as meta-variables. Therefore, the definition of a meta-task specifies the common semantic structure of action verbs in the corresponding Frame. For example, the meta-task *put-Placing* is defined as:

```
( define ( meta-task put-Placing
  ( :parameters ?Agent ?Theme ?Source ?Goal))
  ( :precondition ...)
  ( :postcondition ...)
  ( :invariant ... ) )
```

where all action verbs in Frame *Placing* (e.g., *lay*, *heap*, *deposit*) share the same definition. When a robot tries to plan with *put-Placing* as its action verb (verb sense) for an instruction, our NLP components will try to extract appropriate entities for every semantic roles specified in the definition of meta-task *put-Placing* (See Section V for more detail).

It is worth noting that *common verbs* are normally not explained in the aforementioned open resources because most of them belong to the so-called *General Service List* (GSL) — a list of roughly 2000 most frequent English words [9]. The GSL is taken as the defining vocabulary of dictionaries such as the Longman Dictionary of Contemporary English, based on the notion that words should be defined using “terms less abstruse than the word that is to be explained” [13]. As a result, there are few definitions of the GSL verbs in OMICS or other digital dictionaries.

B. NLP Module

This module maps user instruction in natural language I to the OMICS tables, which contains tuple $\langle task, steps \rangle$ for task-oriented instructions or tuple $\langle desire, task \rangle$ for desire-oriented instructions (See Section IV for more detail). The output is a logical form L to the *Planning* module, containing a frame-semantic representation as:

```
(meta-task take-Taking
 ( :parameters food fridge ) )
```

Specifically, interpreting I to L is done in three steps: 1) *dependency parsing* that analyzes the dependencies of each word in a sentence, 2) *frame-semantic parsing* that identifies the verb’s frame, and 3) *semantic matching and recovering* that fills the semantic roles for a given frame. In Section V, each step will be described in detail.

C. Planning Module

The *Planning* module takes the logical form of user instruction L , online knowledge base (e.g., *Re-FrameNet*, *WordNet*, *FrameNet*), domain knowledge, and robot’s skills as the inputs. The output of the *Planning* module is a high-level plan for the motion planning module.

We employ both *global* and *local* planners in the *Planning* module. The global planner searches through the whole knowledge of task decomposition in OMICS to generate a plan. However, most of tasks in OMICS cannot be decomposed into robot’s primitive actions because many steps in OMICS are referred by common verbs, for which OMICS does not contain decomposition knowledge. For example, verbs such as *take*, *place*, *put*, *get*, and *turn* frequently occur in task steps but there is no knowledge in OMICS about how to execute them by the robot. Therefore, a local planner based on ASP is used for planning based on merely the instruction itself.

Note that the local planner is incapable of generating a plan for under-specification terms in an instruction. Therefore, common verbs referred by the instruction must be specified first in order to generate a plan. Fortunately, semantic dictionaries such as *FrameNet* provide rich knowledge about common verbs. In *Re-FrameNet*, we reorganize the definition of an action verb by a set of precondition, postcondition, and invariant over semantic roles of the action (a.k.a., the functional definition of action). Given this, a planner based on ASP can plan actions for the instruction using the formalized functional definition of an action. Section VI will give more detail about our planning method.

D. Skills and Action Model

For a robot, we define an *Action Model* to specify its skills. Specifically, an Action Model consists of several primitive actions. Each primitive action a is defined by a set of precondition, postcondition and invariant, similar to the definition of a common verb in *Re-FrameNet*. In other words, they specify conditions under which a can be executed, conditions that hold when a finishes, and conditions that must be satisfied during the execution of a respectively. Indeed, a primitive action is the formal specification of a robot skill. As we will show later sections, the Action Model is useful for our system to generate a plan that is executable by the robot.

⁴<https://framenet.icsi.berkeley.edu/fndrupal/>

⁵<http://ai.ustc.edu.cn/en/research/reframenet.php>

Algorithm 1 SolveTask(task t , ActionModel AM)

```

1:  $gSeen := \emptyset$  /* prevent infinite recursive loop when exploratory
   searching itself */
2: initiate  $worldmodel$  and  $plans$ 
3: if  $t \in gSeen$  then
4:   return  $null$ 
5: end if
6:  $gSeen = gSeen \cup t$ 
7:  $subTasks = \text{FindSubTasks}(t)$  /* find subtasks of task  $t$  from the
   Tasks/Steps table in OMICS */
8: for each task  $s$  in  $subTasks$  do
9:   if  $\text{GeneratePlans}(s, AM) = null$  then
10:     $FoundEqualTask = False$ 
11:    while there is a new  $t'$  from the Tasks/Steps table seman-
       tically equivalent to  $s$  do
12:      if  $\text{SolveTask}(t', AM) \neq null$  then
13:         $FoundEqualTask = True$ 
14:         $plans.append(\text{SolveTask}(t', AM))$ 
15:         $wordmodel = \text{simulator}(wordmodel, plans)$ 
16:        break
17:      end if
18:    end while
19:    if  $FoundEqualTask = False$  then
20:      return  $null$ 
21:    end if
22:  else
23:     $plans.append(\text{GeneratePlans}(s, AM))$ 
24:     $wordmodel = \text{simulator}(wordmodel, plans)$ 
25:  end if
26: end for /*successfully planned*/
27: return  $plans$  /* all steps have been solved. */

```

E. Learning Module

In this module, methods such as *log_linear*, *Conditional Random Field* (CRF), *Learn from Demonstration* (LfD) are used to learn robot's low-level skills. Intuitively, the more skills a robot possesses, the more capable it is. For example, unless a robot knows how to pour water to a cup, it cannot finish the high-level task such as "make a coffee" (with the task-step tuple $\langle \text{"make a coffee"}, 0, \text{"put hot water in a cup"}, 1, \text{"pour the coffee"} \rangle$). In this paper, we assume that our robot has all necessary low-level skills to complete a task specified by user instructions though most of the skills must be learned one by one in practice. The learning methods for robot skills are interesting but beyond the scope of this article.

After introducing our system as a whole, we describe our main algorithms for instruction understanding next.

IV. UNDERSTANDING USER INSTRUCTIONS

There are two types of user instructions that we consider in this article: 1) *task-oriented* instruction (e.g., "serve a meal") and 2) *desire-oriented* instruction (e.g., "I am thirsty"). In OMICS, a task-oriented instruction is represented as tuple $\langle t, s \rangle$, where $s = \langle s_1, s_2, \dots, s_n \rangle$ is a sequence of the n steps to complete the task t . For example, given task $t = \text{"serve a meal"}$, a sequence of steps may be $s = \langle s_1 : \text{"take the meal"}, s_2 : \text{"put it on a plate"}, s_3 : \text{"place the plate on a table"} \rangle$. Similarly, a desire-oriented instruction is represented as tuple $\langle d, t \rangle$, where t is the task corresponding to the user desire d . For instance, given user desire $d = \text{"I am thirsty"}$, the task for a robot may be $t = \text{"serve a drink"}$. Indeed, in most of the domestic

Algorithm 2 SolveHelp(desire t , ActionModel AM)

```

1:  $AllHelps := \text{FindHelpsMaptoDesire}(\text{desire } t)$ 
   /* find all help tasks mapped to desire  $t$  */
2: for each help task  $s$  in  $AllHelps$  do
3:   if  $\text{GeneratePlans}(s, AM) = null$  then
4:     for task  $gs$  in Tasks/Steps Table do
5:       if  $gs$  semantically equivalent to  $s$  then
6:         return  $\text{SolveTask}(gs, AM)$ 
7:       end if
8:     end for
9:   else
10:    return  $\text{GeneratePlans}(s, AM)$ 
11:   end if
12: end for
13: return  $null$ 

```

Algorithm 3 GeneratePlans(task t , ActionModel AM)

```

1: /* generate a plan for low-level task  $t$  */
2:  $sem := \text{SemanticMatchAndRecover}(t)$ 
3: if  $sem.frame = NULL$  then
4:   return  $null$ 
5: end if
6: if  $sem.frame \in AM$  then
7:   return  $sem.frame(sem.parameters)$ 
8: else
9:    $gRFN := \text{FindRFNBySem}(sem.frame)$  /* find the defini-
       tion of  $sem.frame$  in Re-FrameNet */
10:   $Res = \text{solver}(gRFN, sem, AM)$  /* compute a plan by in-
       putting rules of gRFN,  $sem$  and  $AM$ . */
11:  if  $Res \neq NULL$  then
12:    return  $Res$ 
13:  else
14:    return  $null$ 
15:  end if
16: end if

```

scenarios, a user instruction is usually either task-oriented or desire-oriented. Now, we turn to our algorithms for generating a plan for these two types of user instructions respectively.

Algorithm 1 is used to process task-oriented instructions by utilizing the *Tasks/Steps* table in OMICS. The input is a naturally expressed task t and the robot's action model AM and the output is a sequence of primitive actions $plans$. Specifically, it first finds all subtasks of task t from the *Tasks/Steps* table of OMICS. Then, it tries to generate a plan (i.e., a sequence of primitive actions) for each subtask. If a plan is successfully generated, the plan is added to the plan list $plans$ and the simulator advances to the next subtask. Otherwise, it searches the *Tasks/Steps* table of OMICS again for all *Semantically Equivalent* (SE) tasks⁶ of that subtask until one of the SE tasks is successfully planned. If there is no SE task or none of the SE tasks can be successfully planned, a $null$ is returned to indicate the failure of task planning. After all subtasks are successfully planned, $plans$ are returned and executed by the robot.

Algorithm 2 is used to process desire-oriented instructions by utilizing the *Help* table in OMICS. Similarly, the input is a desire and an action model and the output is a plan. Specifically, it first finds a list of help tasks offering the

⁶For example, the tasks of "give someone an object" and "take an object to someone" are semantically equivalent.

corresponding help when given a desire. Then, it tries to plan for each of the help tasks by checking whether the help task can be successfully planned with a sequence of primitive actions. If so, the resulting plan is returned. Otherwise, it searches the *Tasks/Steps* table in OMICS for a SE task of the help task and calls Algorithm 1 to generate the plan.

Notice that both Algorithms 1 and 2 depend on Algorithm 3 to generate a plan for a low-level task t . In Algorithm 3, it first performs semantic role matching and recovering for task t and outputs a frame and its roles. If no verb frame is identified, the process terminates with *null* as no plan can be generated. If the frame is a primitive action, this frame plus its roles are returned. Otherwise, the frame is evoked by common verbs. In this case, it first finds the definition of *sem.frame* in *Re-FrameNet* and translate it to a set of rules. After that, it computes a plan based on the rules of *gRFN*, the frame *sem*, and the action model *AM*.

Now, the key procedures in Algorithm 3 are: 1) how to do semantic role matching and recovering given a task expressed in natural language; 2) how to compute a plan given a set of rules, a frame, and an action model. The details about the two procedures are described in Sections V and VI respectively.

V. SEMANTIC MATCHING AND RECOVERING

We propose a three-phase procedure to translate a user instruction expressed in natural language into the internal representation, which can be handled by our planner. Firstly, a probabilistic syntactic parser is used to retrieve the dependencies of the instruction. Secondly, the frame of sentence’s verb is identified by frame-semantic parsing. Here, without loss of generality, we assume that each instruction represents just a single task (verb). Thirdly, the semantic roles of the frame are recovered and filled as much as possible with the matched entities appeared in the instruction or its sentential context, represented as a meta-task in *Re-FrameNet*. More details about our three-phase procedure is described below.

A. Dependency Parsing

We use the Stanford parser [14] in the first phase, which produces the Stanford-typed dependencies between words in a sentence. These dependencies indicate the grammatical relations between words in terms of the name of relation, governor, and dependence [15]. Figure 3 illustrates the parsing of a sentence “take food out of refrigerator”. The edge of the type *dobj* denotes that the noun “food” is the direct object of the verb “take”. The verb “take” also governs the noun “refrigerator” via the typed dependency *prep_out_of*. Since the typed dependency between a verb and a noun reveals their semantic-role relation, the syntactic structure of an instruction is used for our semantic role matching and recovering.

B. Frame Semantic Parsing

Given that a verb varies in different senses, an instruction may represent different meanings and therefore can be mapped to different frames in *FrameNet*. For instance, the verb “take” can represent the Frame *Bring* or *Removing* under different

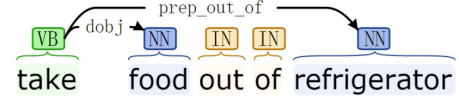


Fig. 3. Stanford typed dependencies of “take food out of fridge”.

contexts. The Stanford parser does not disambiguate verb senses. Therefore, we propose a *Frame Semantic Parsing* method to map a verb to a unique Frame. Specifically, we define a frame identification model and train the model with sets of data from *FrameNet* and OMICS as below.

1) *Model*: Given a sentence $\mathbf{x} = \langle x_1, \dots, x_n \rangle$ with frame-evoking verb v , we seek the most likely Frame f^* in the frame identification stage. Let \mathcal{F} be the set of candidate Frames for v , \mathcal{L} the set of verbs found in the *FrameNet* annotations, and $\mathcal{L}_f \subseteq \mathcal{L}$ the subset of verbs annotated by evoking the Frame f . The frame identification can be formalized by the following prediction rule:

$$f^* = \arg \max_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}_f} p(f, l | v, \mathbf{x})$$

For $f \in \mathcal{F}$ and $l \in \mathcal{L}_f$, a conditional log-linear model is used to model the probability $p(f, l | v, \mathbf{x}; \theta)$:

$$p(f, l | v, \mathbf{x}; \theta) = \frac{\exp[\theta \cdot \Phi(f, l, v, \mathbf{x})]}{\sum_{f' \in \mathcal{F}} \sum_{l' \in \mathcal{L}_{f'}} \exp[\theta \cdot \Phi(f', l', v, \mathbf{x})]}$$

where $\theta \cdot \Phi(f, l, v, \mathbf{x})$ is the inner product $\sum_{i=1}^M \theta_i \times \Phi_i(f, l, v, \mathbf{x})$ and θ is the parameter vector over the feature function Φ with M dimension.

Generally, the feature function allows for a variety of (possibly overlapping) features. A feature Φ_i may relate a frame f to a verb v , representing a lexical-semantic relationship.

2) *Data*: Our training and test sets come from *FrameNet* lexicon and OMICS. The *FrameNet* lexicon is a taxonomy of manually identified general-purpose Frames in English. Listed in the lexicon with each Frame are several lemmas (with part of speech) that can denote the Frame or some aspect of it — these are often called *Lexical Units* (LUs). Table I shows some examples of our training and test sets.

3) *Training*: Given the training subset of the data in the form $\langle x^j, v^j, f^j, s^j \rangle_{j=1}^N$ where N is the number of sentences, we discriminatively train the frame identification model by maximizing the following log-likelihood function:

$$\max_{\theta} \sum_{j=1}^N \log \sum_{l \in \mathcal{L}_f^j} p(f^j, l | v^j, \mathbf{x}^j).$$

Specifically, we optimize it using a distributed version of gradient ascent algorithm with initial value $\vec{\theta}$ as:

for $k = 0..D - 1$

for $i = 1..M$

$$\theta_i = \theta_i + \alpha \frac{\partial \sum_{j=1}^N \log \sum_{l \in \mathcal{L}_f^j} p(f^j, l | v^j, \mathbf{x}^j)}{\partial \theta}$$

TABLE I
DATA COLLECTED FROM FRAMENET AND ANNOTATED FROM OMICS.

Data	Size	Examples	Verb	LU	Frame
FrameNet	191740	i want to bring your daughter up to the prison	bring	bring.v	Bringing
		i was visited by one of the king 's most important officials	visited	visit.v	Arriving
		cutting his wrist and jumping from a third-floor window	cutting	cut.v	Cause_harm
OMICS	1100	remove objects from surface	remove	remove.v	Removing
		complete the dance together	complete	complete.v	Activity_finish

TABLE II
HEURISTIC RULES FOR SEMANTIC ROLE FILLING WITHIN SENTENCE.

Meta-task	Dependency Type	Semantic Role
put-Placing	dobj	Theme
put-Placing	prep_in	Goal
take-Removing	dobj	Theme
take-Removing	prep_from	Source
dry-Cause_to_be_dry	dobj	Dryee
deliver-Delivery	prep_to	Recipient
...		

TABLE III
PART OF HIERARCHY FOR *take-taking*.

Semantic Role	Class
Theme	Holdable_Obj
Source	Supportable_Obj \sqcup Containable_Obj

where D is a parameter that controls the number of passes over the training data, M is the number of features, and N is the total size of our training set.

Note that the computational complexity of the algorithm above is $O(D \times M \times N)$. When the number of features is large, it will be costly to train our model sequentially. In order to update the parameter of a feature f faster, we consider N_f training examples that contains only f instead of N . Hence, the computational complexity becomes $O(D \times M \times N_f)$, where N_f is usually much smaller than N .

C. Roles Matching and Recovering

After the Frame for the meta-task achieved from *Re-FrameNet* is identified, the semantic roles of the meta-task must be filled with the corresponding entities (expressed by nouns) in the sentence or from its sentential context. In Figure 4, given steps $\mathbf{s} = \langle s_1, \dots, s_n \rangle$ and Frames of each step $\mathbf{f} = \langle f_1, \dots, f_n \rangle$, we match and recover missing semantic roles of each Frame $\mathbf{r} = \langle r_1, \dots, r_n \rangle$, where $r_i = \langle r_{i1}, \dots, r_{ik_i} \rangle$.

$$\begin{aligned}
 s_1 &: \text{frame}(f_1), \text{role}(r_{11}), \text{role}(r_{12}), \dots, \text{role}(r_{1k_1}) \\
 s_2 &: \text{frame}(f_2), \text{role}(r_{21}), \text{role}(r_{22}), \dots, \text{role}(r_{2k_2}) \\
 &\dots \\
 s_n &: \text{frame}(f_n), \text{role}(r_{n1}), \text{role}(r_{n2}), \dots, \text{role}(r_{nk_n})
 \end{aligned}$$

Fig. 4. Formalization description of instruction flow.

Take the flow of instructions \langle step 1: “go to fridge”; step 2: “open the fridge door”; step 3: “take the beer”; step 4: “close the fridge door” \rangle for example. The third instruction (i.e., step 3) is identified as the meta-task *take-Taking*, whose semantic roles in *Re-FrameNet* include *Agent*, *Theme*, and *Source*. However, this instruction only explicitly specifies the role *Theme* (*the beer*), while the others are missing from it. Note that the semantic role *Source* can be recovered and matched with the entity *fridge* in the sentential context of this instruction. Therefore, the challenge of our third phase lies in the recovering of missing semantic roles.

To address this challenge, we borrow ideas from the “last objects” method [16] and propose the following method:

- 1) For any semantic role r that is defined in *Re-FrameNet* but missing from a sentence s , an entity e that matches r according to the definition and has less sentential distance from s is preferable to be the value of r . Here, the sentential distance between e and r is defined as $(n-m)$, if e and r appear in the m -th and n -th sentences in the same sentence flow respectively, with $m \leq n$. For $1 \leq k \leq n$, it is formalized as: $r_{ki} = \arg \min_{e \in r_i} (k-l)$, if r_{ki} is missing and e matches r_{ki} .
- 2) If a semantic role r cannot be recovered through 1), it is assumed that (the value of) r is unspecified in the sense that any entity satisfying the *Re-FrameNet* definition of r is a default value of r under the given context⁷. For instance, the *Source* role of single sentence “put beverage in the fridge” is unspecified and thus any entity in the class *beverage* can be taken as the value of *Source* under the context of this sentence. Obviously, all missing semantic roles of the first sentence in a flow of instructions are unspecified. In fact, given a context, not all of the semantic roles specified in *FrameNet* or *Re-FrameNet* are necessary for naturalistic language instruction understanding and task planning.

In general, we divide semantic matching and recovering into two cases. The first case is for zero sentential distance, i.e., recovering semantic roles based on the instruction itself. Table II shows some heuristic rules for this case, each assigning a noun of the designated dependence type to a semantic role of a meta-task. For example, according to the first rule in Table II, *beverage* is assigned to the semantic role *Theme* of the meta-task *put-Placing*. Similarly, *fridge* is assigned to *Goal* of the same meta-task according to the second rule. After matching, the single instruction “put beverage in the fridge” is interpreted as an instantiated meta-task of *put-Placing* as follow:

```

( define ( meta-task put-Placing
  ( :parameters robot beverage null fridge))
... )

```

In the case where a semantic role of a sentence cannot be identified within the sentence, semantic matching is conducted

⁷Some of unspecified roles should be identified by grounding [17], [6], [18], [19], which is beyond the scope of this article.

TABLE IV
PART OF HIERARCHY FOR CLASSES.

Class	Subclass	Subsubclass
Object	Containable_Obj	<i>fridge</i>
Object	Holdable_Obj	<i>beer, beverage</i>
Object	Supportable_Obj	<i>table</i>

based on a taxonomical hierarchy, which specifies what sorts of entities can be taken as values by a semantic role. For example, the *Theme* role of meta-task *put-Placing* should take a holdable object for the robot. Table III shows a part of the hierarchy about meta-task *take-Taking*. Moreover, the hierarchy needs to be extended by class-subclass relationships, as exemplified in Table IV. Consider the example sentence “take the *beer*” in Figure 2. The entities appeared in the context are *fridge* and *fridge-door*. In our taxonomical hierarchy, *fridge-door* is an instance of *door* which is neither supportable nor containable. Therefore, only *fridge* can be a value of the *Source* role of *take-Taking*. In the case of multiple candidates for a semantic role, the nearest entity will be selected. The high-level part of our hierarchy is similar to that of AfNet [18]. This is beneficial to integrating grounding mechanism into our prototype system.

VI. TASK PLANNING WITH ASP

Given the meta-task semantic representation of a sentence, we generate an action sequence using OMICS and functional definition knowledge of common verbs (e.g., *Re-FrameNet*). In our previous work, we proposed the *OK-planner* [8] based on ASP. In this approach, all types of knowledge are converted into ASP and then an ASP solver is applied to generate an action sequence. However, this work does not consider *common verbs* for handling complex tasks.

In this article, we built our planner upon our previous work but additionally consider the following challenges: 1) how to define the functional knowledge of primitive actions in *Action Model* and 2) how to convert *Re-FrameNet* definition of common verbs into ASP.

A. Planning with Action Model

As aforementioned, we specify robot skills in our system by an action model, i.e., a set of primitive actions that are executable for the robot. Table V shown some basic definition of the primitive actions for a typical service robot though different types of robots may have different action model. Formally, each primitive action a is defined as a pair $\langle pre(a), eff(a) \rangle$, where $pre(a)$ and $eff(a)$ are the preconditions and effects of a respectively. For instance, `moveto(obj)` is a primitive action that tells the robot to move close to the specified object `obj`. The pre and eff of `moveto(obj)` show whether the robot is near the specified `obj` before and after the `moveto` action respectively.

Given any initial state s_0 and a possible plan a_1, \dots, a_n , an action model determines a predicted trajectory $\tau^* = \langle s_0, a_1, s_1, \dots, a_n, s_n \rangle$ through inference for all the states s_1, \dots, s_n along with the execution of the action sequence during planning. For instance, given an instruction “get food from fridge”, we need to generate a plan for the robot as:

TABLE V

Primitive Action(a)	Description(a), $pre(a)$, $eff(a)$
<code>moveto(obj, t)</code>	Move to <code>obj</code> by using motion planner at time t . $pre(a) : not\ near(robot, obj, t - 1)$ $eff(a) : near(robot, obj, t)$
<code>find(obj, t)</code>	Find <code>obj</code> in the environment by using vision at time t . $pre(a) : near(robot, obj, t - 1)$ $eff(a) : belivelocation(robot, obj, t)$
<code>pick_up(obj, t)</code>	pick up <code>obj</code> by using robotic arm at time t . $pre(a) : near(robot, obj, t - 1)$ $pre(a) : belivelocation(robot, obj, t - 1)$ $eff(a) : grasping(robot, obj, t)$
<code>put_down(obj, t)</code>	put down <code>obj</code> on a plane in front of robot at time t . $pre(a) : grasping(robot, obj, t - 1)$ $eff(a) : not\ grasping(robot, obj, t)$
<code>open(obj, t)</code>	open the <code>obj</code> at time t . $pre(a) : closed(obj, t - 1)$ $eff(a) : opened(obj, t)$
<code>close(obj, t)</code>	close the <code>obj</code> at time t . $pre(a) : opened(obj, t - 1)$ $eff(a) : closed(obj, t)$

```
moveto(fridge, 1), open(fridge, 2),
find(food, 3), pick_up(food, 4),
close(fridge, 5).
```

Note that the semantic representation of a user instruction can be easily converted into a ASP form [8]. All we have to do is to fill sufficient knowledge for the ASP planner. Using our *Re-FrameNet* definition, an action verb is reorganized by a set of precondition, postcondition, and invariant over semantic roles of the action. Therefore, the remaining problem for our approach is how to convert the functional definitions of common verbs into ASP.

B. Conversion of Functional Knowledge

Let α be a common verb (word sense). The set of linguistic variables of α 's frame is denoted by $\Theta(\alpha)$. The set of properties and relations over $\Theta(\alpha)$ occur in the functional definitions of verbs belonging to α 's Frame is denoted by $\Sigma(\alpha)$. Given a task $task_\alpha$ based on the common verb α as:

$$(:\text{meta-task } \alpha \text{ } (: \text{parameters } (p_1 \mathcal{X}) \cdots (p_h \mathcal{X})))$$

where $X_1, \dots, X_h \in \Theta(\alpha)$ and p_1, \dots, p_h are predicates over a set \mathcal{X} of variables, each constraint of the common verb α can be converted to a set of ASP rules w.r.t. the task $task_\alpha$ as:

1. A precondition

$$(:\text{precond } \alpha \text{ } (\text{conj } (\text{disj } l_1 \cdots l_n) \cdots (\text{disj } l'_1 \cdots l'_m)))$$

is converted to the following ASP rules:

$$\begin{aligned} &\leftarrow process(task_\alpha, t, t'), not\ true(l_1, t), \dots, not\ true(l_n, t), \\ &\quad t < t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \\ &\dots \\ &\leftarrow process(task_\alpha, t, t'), not\ true(l'_1, t), \dots, not\ true(l'_m, t), \\ &\quad t < t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \end{aligned}$$

2. A postcondition

$$(:\text{postcond } \alpha \text{ } (\text{conj } (\text{disj } l_1 \cdots l_n) \cdots (\text{disj } l'_1 \cdots l'_m)))$$

is converted to the following ASP rules:

$$\begin{aligned} &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l_1, t'), \dots, \text{not true}(l_n, t'), \\ &\quad t < t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \\ &\dots \\ &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l'_1, t'), \dots, \text{not true}(l'_n, t'), \\ &\quad t < t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \end{aligned}$$

3. An invariant

(:invariant α (conj (disj $l_1 \dots l_n$) \dots (disj $l'_1 \dots l'_m$)))

is converted to the following ASP rules:

$$\begin{aligned} &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l_1, t''), \dots, \text{not true}(l_n, t''), \\ &\quad t < t', t \leq t'', t'' \leq t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \\ &\dots \\ &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l'_1, t''), \dots, \text{not true}(l'_n, t''), \\ &\quad t < t', t \leq t'', t'' \leq t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \end{aligned}$$

4. An invariant

(disj (:invariant α (conj (disj $l_1 \dots l_n$) \dots (disj $l'_1 \dots l'_m$)))
(:invariant α (conj (disj $l_1^* \dots l_n^*$) \dots (disj $l'^*_1 \dots l'^*_m$))))

is converted to the following ASP rules:

$$\begin{aligned} f &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l_1, t''), \dots, \text{not true}(l_n, t''), \\ &\quad t < t', t \leq t'', t'' \leq t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \\ &\dots \\ f &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l'_1, t''), \dots, \text{not true}(l'_n, t''), \\ &\quad t < t', t \leq t'', t'' \leq t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \\ f^* &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l_1^*, t''), \dots, \text{not true}(l_n^*, t''), \\ &\quad t < t', t \leq t'', t'' \leq t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \\ &\dots \\ f^* &\leftarrow \text{process}(\text{task}_\alpha, t, t'), \text{not true}(l'^*_1, t''), \dots, \text{not true}(l'^*_n, t''), \\ &\quad t < t', t \leq t'', t'' \leq t', p_1(\mathcal{X}), \dots, p_h(\mathcal{X}) \\ &\leftarrow f, f^* \end{aligned}$$

After all pieces of knowledge have been converted into the ASP rules, an ASP solver *iclingo* [20] — a combination of *Gingo* and *clasp* for incremental grounding and solving — is used to incrementally ground the ASP rules above and search for answer sets, from which a plan can be computed [8].

VII. EXPERIMENTS

We empirically evaluate our system with three experiments. The first experiment was devised to investigate the performance of our SMR (i.e., Semantic Matching and Recovering) method. The second experiment aimed to testing the performance of the whole system when different open knowledge bases were used. We also analyzed the main factors that may affect the performance. Finally, we demonstrate that how our approach can be deployed in our KeJia robot to solve instruction understanding problems in two domestic scenarios. Additionally, we also present our long-term effort on applying the proposed technique in the RoboCup@Home competitions.

TABLE VI
RESULTS OF TRANSLATION OVER TWO TESTSETS OF FRAME NET AND OMICS.

Syntactic	Data	P	R	F
Verb	OMICS	97.61	81.83	89.03
Entities	OMICS	80.32	67.33	73.25
Identification	Data	P	R	F
Frame	OMICS	84.31	61.43	71.07
Frame	FrameNet	80.98	79.05	80.00
Semantic Roles	OMICS	78.00	53.71	63.62

A. Experiments with SMR

To test our SMR method, we collect 191,740 examples annotated with frame-semantic structures for the frame identification model from *FrameNet* lexicon and 470 examples from OMICS. Then, we parse each sentence by the Stanford parser. Finally, we only select those examples whose LU is a verb or a verb phrase. As a result, the training data contains 70,149 examples and the test data contains 18,183 examples from *FrameNet* and 630 examples from OMICS. In our experiments, the frame identification model instantiates 76,289 binary features.

Table VI shows the results on each part of translation of hierarchical instructions. The performance is evaluated by *Precise* (P), *Recall* (R), *F1* (F) defined as: $Precise = TP / (TP + FP)$, $Recall = TP / T$, $F1 = 2 * Precise * Recall / (Precise + Recall)$, where TP stands for the number of the sentences parsed correctly, FP is the number of the sentences parsed wrongly, and T is the total length of the dataset.

As we can see from the results, syntactic results have a very high precise and $F1$ value, which benefits to the meta-task identification phase. However, it does not disambiguate the meaning of a verb (e.g., the verb “get” has two meanings: “Getting: get the food” and “Motion: get to the room”). The meta-task identification, which obtains a $F1$ value of 80 over the *FrameNet* data and 71.07 over the OMICS data. Moreover, the overall performance of the whole translation system maintains a quite high precise and relatively low recall due to the data sparseness and one meta-task assumption.

B. Experiments on OMICS

The experiments on OMICS were divided into two tests. Test 1 was conducted on 11,885 user tasks from the *Tasks/Steps* table and Test 2 on 467 user desires from the *Help* table.

Test 1 consisted of four rounds. In the first round, only the definitions of the 11,885 tasks from the *Tasks/Steps* table and a small action model *AM* representing the basic perception and manipulation skills of a robot were used. Specifically, *AM* contained only 6 primitive actions: *move*, *find*, *pick_up*, *put_down*, *open*, and *close*. Synonymy knowledge from *FrameNet* was used into the second to fourth rounds of Test 1. In the third and fourth rounds, rewritten knowledge from *Re-FrameNet* was considered with our SMR technique. However, in the third round, missing roles were not recovered from the context.

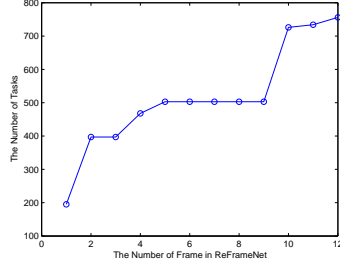
Table VII shows the experimental results of Test 1. The second row shows the numbers of tasks that were successfully planned by the *global* planner with tasks/steps in the four rounds. The third row shows the total numbers of tasks that were successfully planned in the four rounds. The fourth

TABLE VII
EXPERIMENTAL RESULTS OVER 11885 USER TASKS.

Test 1	AM	FN	SMR_0	SMR_1
Tasksteps	134	150	618	790
Tasksteps+	157	174	756	935
Percent(%)	1.32	1.46	6.36	7.87
GroundTruth(%)	*	*	63.75	64
TruthPercent(%)	1.32	1.46	4.05	5.04

Frame	Planned Number
Getting	195
Placing	397
Bringing	397
Removing	468
Cause_motion	503
Locating	503
Self_motion	503
Mass_motion	503
Waiting	503
Taking	726
Giving	734
All RFN	756

(a)



(b)

Fig. 5. Influences of the Frame in Re-FrameNet in Test 1.

row shows the percentages of successfully planned tasks with respect to the total number of tested tasks. Since there are no ground truth data for OMICS, we randomly drew 80 and 100 samples from the last two rounds respectively and verified them manually. It turned out that 51 and 64 samples among them were correct. As shown in the fifth row of Table VII, the correctness percent decreased when *Re-FrameNet* was used; but the number of correctly planned tasks still increased remarkable. Moreover, we can see that the overall performance improved when semantic roles of common verbs was used, much better than the state-of-art solution [8].

As shown in Figure 5, the number of the successfully planned tasks gradually increased when more frames were added to the algorithm. It also shows that some frames cannot be mapped into robots' action (i.e., *Mass_motion* and *Waiting*). The main reason is the limit of robots' primitive actions.

Table IX reports the main types of failures that we observed in Test 1. Specifically, the *Parsed Failure* occurred in 3027 tasks because the semantic matching and recovering procedure failed to retrieve any frame from *Re-FrameNet* (RFN) for a task. The *RFN Failure* occurred in 4394 tasks due to the fact that *Re-FrameNet* contains only 43 frames, in which 7421 tasks cannot be used to generate a plan by the robot. A *Global Planning Failure* occurs when a task/step t cannot be planned and none of the following conditions hold: t is a primitive action, semantically equivalent to meta-task in *Re-FrameNet* or another task in the *Tasks/Steps* table. In total, there were 3527 tasks failed in this category. A *Local Planning Failure* occurs when the *solver* (in Algorithm 3) is launched but fails to generate any plan. Further study reveals that these two sorts of planning failures are mainly due to lack of knowledge/skills.

Test 2 was conducted on 467 user desires from the *Help* table of OMICS. The experimental results are shown in Table VIII. As we can see, the success rates were higher than the corresponding rounds of Test 1. In particular, the success rate is as high as 81% in the last round. This is because a desire can be met by various tasks, which can be different

TABLE VIII
EXPERIMENTAL RESULTS OVER 467 USER DESIRES.

Test 2	AM	FN	SMR_0	SMR_1
Help	244	247	299	331
Help+Tasksteps	254	261	358	379
Percent(%)	54.39	55.89	76.66	81.16

TABLE IX
INFLUENCES OF MAIN FACTORS OF FAILURE IN TEST 1.

Failure	Number	Percent (%)
Parsed Failure	3027	26.7
RFN Failure	4394	38.8
Global Planning Failure	3527	31.2
Local Planning Failure	378	3.3

from one another. Therefore, knowledge used in the rounds of Test 2 was much richer than that in Test 1.

Notice that the overall performance increased about 5 times in Test 1 and 50% in Test 2 when semantic roles of common verbs and *Re-FrameNet* was used. There are two main reasons for this improvement. Firstly, rewritten knowledge of common verbs in *Re-FrameNet* fills knowledge gaps caused by lack of definitions of these verbs in OMICS. Without the knowledge, 761(=935-174) tasks would not have been successfully planned in the last two rounds of Test 1. Secondly, our SMR mechanism contributed significantly to the improvement. Without it, 179(=935-756) out of these 761 tasks would not have been successfully planned. In other words, *Re-FrameNet* and SMR made about 76% and 24% contributions to the improvement of success rate in task planning respectively.

C. Case Study on KeJia Robot

We conducted a case study of our system with the KeJia robot. As shown in Figures 6 and 7, our KeJia robot is based on a two-wheels driving chassis of 62cm×53cm×32cm and the equipped sensors include a laser range finder, a 1394 camera, and a Kinect. A lifting system is mounted on the chassis attached with the robot's upper body. Assembled with the upper body is a 6 DOF arm. It is able to reach objects over 83cm far from mounting point and the maximum payload is about 500g. The robot's power is supplied by a 20Ah battery that guarantees the continuous running of at least 1 hour. The computational resources consist of a laptop and an on-board PC. Our system is built upon existing modules including motion control for the mobile base and arm, navigation, recognition and localization.

In our case study, we first tried two typical scenarios where the robot can benefit from the proposed techniques. Then, we introduce our long-term effort on developing general-purpose systems for user instruction understanding in the annual RoboCup@Home competitions.

1) *Scenario 1*: As shown in Figure 6, a toy and a toy box were placed on the floor. Our KeJia robot was asked by a user to "clean up toys". Note that, with only this instruction, the robot is unable to complete the task because the action "clean up" is unspecified. In our system, the robot first extracted the subtasks of the task "clean up toys" based on the knowledge in OMICS. By doing so, a tuple of $\langle \text{task. "clean up toys": step 1. "pick up toys from floor"; step 2. "put toys in toybox".} \rangle$ was generated. Then, our SMR method matched and recovered

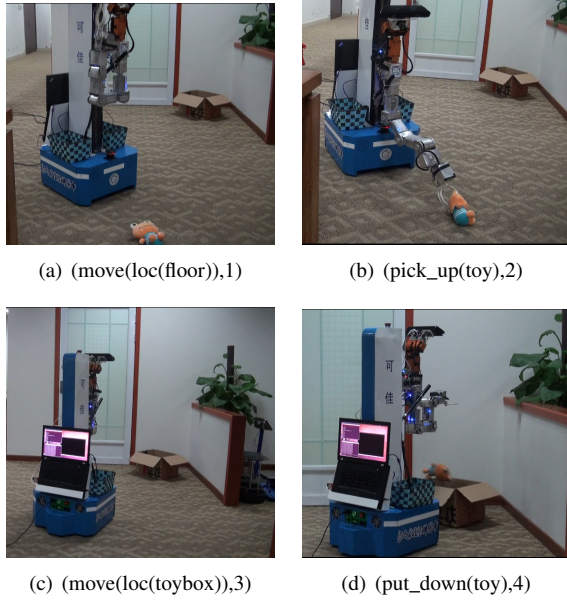


Fig. 6. Execution of the task “clean up toys” in tasksteps. subfigure (a) and (b) are plans for “pick up toys from floor”, (c) and (d) for “put toys in toybox”.

semantic roles of each step in the tuple as:

```
( define ( task clean_up (toys)
  ( :subtasks pick_up-Pick_up
    ( :parameters toys floor))
  ( :subtasks put-Placing
    ( :parameters toys floor toybox))))
```

After that, our planner sequentially processed each subtask. In this phase, since the action *pick_up* is a primitive action, the subtask *pick_up* can be directly executed by our robot. For the second subtask, we tried to generate a plan given the definition of the meta-task *put-Placing* as:

```
( define ( meta-task put-Placing
  ( :parameters ?Agent ?Theme ?Source ?Goal))
  ( :precondition (at Theme Source))
  ( :precondition (conj(portable Theme)(object Theme)))
  ( :postcondition (at Theme Goal)))
```

In this scenario, the plan generated by the planner for this task is shown in Figures 6(c) and 6(d). At this point, the task “clean up toys” is solved by our system and finally the entire plan is executed by the robot to complete the task.

2) *Scenario 2*: As shown in Figure 7, a user spoke to the robot that he “have a headache”. This was identified as a user desire. Similar to the previous scenario, our system first extracted a series of help tasks for the user desire such as “with pain medication”, “give them an aspirin”, etc. Then, our SMR method matched and recovered semantic roles of each help task. In this scenario, our planner failed to plan for the task “with pain medication” but successfully recovered the *Source* elements and generated a plan for the task “give them an aspirin”. A list of actions for the plan of this task are illustrated in Figure 7.

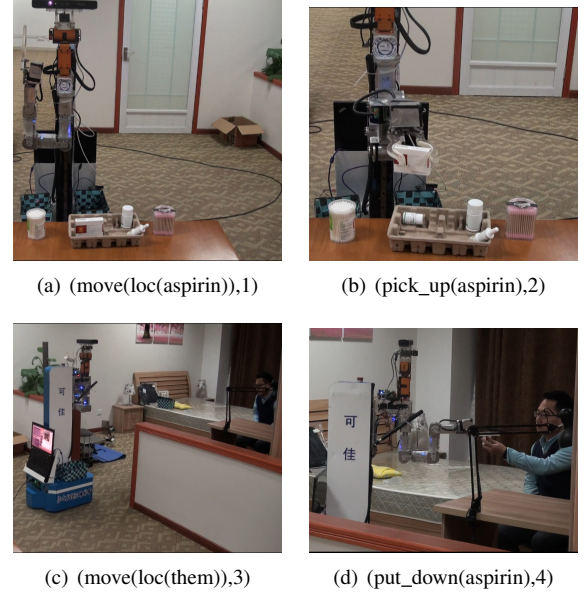


Fig. 7. Execution of “give them an aspirin” for the desire “have a headache”.

TABLE X
SCORES OF ALL ROBOCUP@HOME BENCHMARK TESTS.

Competition	top 1	top 2	top 3	top 4	top 5
RoboCup 2013	4767	4645	3622	3155	3066
Team Name	WE	NimbRo	TU/e	Homer	BORG
RoboCup 2014	9305	5701	5656	4842	3417
Team Name	WE	TU/e	NimbRo	Tobi	Pumas
RoboCup 2015	750	651	647	562	359
Team Name	WE	Homer	TU/e	Tobi	Pumas

A video demon for the two scenarios above with our KeJia robot is given at: <https://youtu.be/A4GBXHG0174>

3) *RoboCup@Home*: This is an international annual competition for domestic service robots and is part of the RoboCup event. In this competition, a set of benchmark tests are proposed to evaluate the robots’ abilities and performance in a realistic non-standardized home environment setting. The most related benchmark test to this article is the *General Purpose Service Robot* (GPSR) test, which requires a robot to solve tasks upon request in natural language randomly generated by the referees during the competition.

In the RoboCup@Home competitions of the past three years, our team — WrightEagle (WE) [21] got the 1st place once and 2nd place twice. Table X shows the total scores of the top 5 teams in the benchmark tests (without the final stage). It can be seen from the results that our team (i.e., WE) performed very well in the competitions. Particularly, in the GPSR tests, the performance of our system was competitive comparing to other top teams as shown in Table XI.

Although there are generally many factors contributing to the success in the RoboCup@Home competitions, our robot did benefit substantially from the proposed system as described in this article to process user instructions and generate plans. The competitions motivated us to develop a general-purpose system for understanding user instructions in natural language and also provide a good testbed for such systems.

TABLE XI
SCORES OF THE GPSR BENCHMARK TESTS.

GPSR Test	top 1	top 2	top 3	top 4	top 5
RoboCup 2013	900	500	450	250	250
Team Name	NimbRo	Pumas	WE	TU/e	Tobi
RoboCup 2014	750	700	500	0	0
Team Name	WE	NimbRo	TU/e	Tobi	Pumas
RoboCup 2015	105	60	30	30	20
Team Name	Tobi	WE	TU/e	Homer	Skuba

VIII. RELATED WORK

To date, many approaches on instruction understanding and task planning for service robots have been proposed in the literature. For instance, several integrated systems [2], [16], [22] for natural language understanding have been introduced to enable robots to complete tasks given instructions in natural language. However, they all assume that instructions are definitely specified for the domains and do not consider semantic disambiguation of verbs and their roles. Work have been proposed to manually create environment-driven instructions for grounding user instructions in natural language to robots' actions [10], [23]. However, these methods cannot scale to large number of tasks because each task need to be manually specified in an environment, and are not suitable for different types of robots (e.g., robots with different arm configurations).

To improve generality and scalability, researchers have tried to exploit online knowledge and learn large-scale knowledge representations to build a general-purpose system for instruction understanding. For example, Lemaignan *et al.* [24], [25] have tried to understand and reason about knowledge around an action model using online knowledge for robots. It is worth pointing out that we previously proposed an integrated system [8] for our KeJia robot consisting of multi-mode NLP, integrated decision-making, and open knowledge searching.

The approaches that are most related to ours are the ones using OMICS for robots to complete household tasks. The first attempt to utilize OMICS to accomplish a household task is [26], which proposed a generative model based on the Markov chain techniques. Later on, [27], [28], [29] presented a system called KNOWROB for processing knowledge in order to achieve more flexible and general behavior. Most recently, we proposed a formal description of knowledge gaps between user instructions and local knowledge in robotic system for instruction understanding [30], [8], [31], [32]. However, in these efforts using OMICS for robot task planning with user instructions, *common verbs* are normally not defined in the knowledge base, which limits their performance on utilizing existing open knowledge. Thus, our work is proposed to address the weakness of state-of-the-art methods.

IX. CONCLUSIONS

This article proposed a general-purpose system for service robot handling large-scale user instructions in natural language. The key problem that we addressed is how to map primitive tasks into robot actions using semantic roles of common verbs provided by semantic dictionaries — a common resource of open knowledge in linguistics. To solve this problem, we proposed a novel approach for semantic matching

and recovering. Furthermore, we utilized semantic roles of common verbs defined in semantic dictionaries for handling underspecification of naturalistic language instructions in task planning. Empirical evaluation and analysis were made and show good performance with two test sets consisting of 11885 user tasks and 467 user desires collected from OMICS. Moreover, we developed a prototype system deployed on our KeJia robot and demonstrated our techniques with two typical scenarios. Notably, our system has been used in the RoboCup@Home competitions and shown good performance in the benchmark tests over the past three years.

Here, we conclude with the following findings:

- 1) Overall performance of our system can be improved when *Re-FrameNet* was used. As shown by our experimental results, both the knowledge in *Re-FrameNet* and the SMR technique contributed to the improvement, indicating that rewritten knowledge of common verbs and recovering semantic roles from context are useful for naturalistic instruction understanding and planning.
- 2) The computational efficiency of our system can be improved using the hierarchism of user instructions and knowledge. As shown by our case study, instruction understanding and task planning can be done for our robot in realtime, given that task decomposition knowledge such as OMICS was used for efficient global planning and costly local planning was limited only to small number of low-level tasks defined in *Re-FrameNet*.

In the future, we plan to develop techniques to learn extra knowledge unavailable from user input, such as knowledge about robot manipulation, action configurations in finer degrees other than semantic role, and most importantly grounding. Moreover, we will investigate methods to automatically generate a large set of *Re-FrameNet* for robot tasks.

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